



RESEARCH ARTICLE

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AN INTELLIGENT SLEEP-BASED MACHINE LEARNING SYSTEM FOR CONTINUOUS AND NON-INTRUSIVE HUMAN STRESS LEVEL DETECTION

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ABSTRACT

Machine learning-based human stress detection from sleep patterns leverages wearable-generated physiological and behavioural sleep indicators, including sleep duration, heart rate variability, nocturnal body movement, and sleep stage distribution, to enable objective, continuous evaluation of stress state. Nevertheless, the actual wearable sleep data are usually noisy, incomplete, and highly heterogeneous across individuals, limiting the reliability of features and hindering generalisation. To overcome these problems, this paper proposes a combined sleep-based stress detection model that integrates multiple smart learning modules. The first step is a Robust Wearable Sleep Data Preprocessing Network (RWSD-PN) that performs adaptive noise reduction, missing-value processing, and signal standardisation to improve data quality. This is followed by the Sleep Attribute Impact Quantification Model (SAIQ-M), which is used to assess the relative importance of sleep variables to prioritize informative physiological indicators. It is then processed into a Deep Physiological Sleep Representation Network (DPSR-Net) that produces high-level multivariate representations of intricate sleep-stress interaction patterns, both nonlinear and temporal. In order to enhance further efficiency, the most discriminative and non-redundant subset of features is selected based on the Hybrid Swarm Learning (MSFO-HSL), which results in the diminishing of dimensionality and the threat of overfitting. Lastly, a Transformer-Guided Sleep Stress Classification Network (TG-SSCN) is a model based on attention-guided learning that estimates feature dependencies and correctly classifies stress levels. Through experimental analysis, the framework can be shown to have high predictive performance, including Accuracy, Precision, Recall, F1-Score, and AUC, thereby enhancing robustness, scalability, and reliability. The framework offers an unobtrusive, data-driven, continuous human stress monitor in real-world conditions.



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I. INTRODUCTION

Recent advancements in wearable technology and artificial intelligence have significantly transformed the landscape of human stress detection [1]. Machine learning-based stress monitoring systems are increasingly being developed to analyse physiological and behavioural signals for continuous and objective assessment. Comparative algorithmic studies emphasise the importance of robust and scalable computational frameworks for reliable stress classification. Sleep has emerged as a critical behavioural indicator of psychological well-being [2]. Variations in sleep stages, autonomic regulation, and physiological rhythms are strongly associated with stress adaptation mechanisms. Accurate modelling of sleep-stage transitions and architecture enables improved understanding of mental health conditions. Environmental and physiological modulation of sleep further influences stress responses [3]. Research demonstrates that thermal exposure, photic stimulation, and circadian rhythm adaptation significantly alter sleep quality and autonomic balance. These findings reinforce the importance of incorporating multidimensional sleep parameters in stress detection systems. Standardised sleep scoring methodologies have improved the reliability of sleep-related assessments. Updated evaluation frameworks support precise identification of cyclic alternating patterns and microstructural sleep events. Such structured scoring enhances the quality of feature extraction for machine learning-based stress modelling [4].

Predictive machine learning approaches have also been applied to mental health and sleep-related outcomes. Data-driven models demonstrate the feasibility of forecasting sleep disturbances and stress-linked behavioural patterns using physiological and psychological indicators [5]. Deep learning architectures, particularly convolutional neural networks with attention mechanisms, have shown strong performance in detecting neurophysiological differences associated with mental fatigue and stress. Multimodal signal integration improves classification robustness under complex real-world conditions [6]. Population-based studies highlight associations between sleep consistency, behavioural patterns, and stress-related disturbances across diverse demographic groups [7]. These findings underscore the importance of integrating lifestyle and physiological variables into comprehensive stress-detection frameworks. Despite these advancements, challenges remain in managing noisy wearable data, heterogeneity, and feature redundancy. Therefore, there is a growing need for unified, attention-driven, and optimisation-based machine learning frameworks capable of accurately modelling complex sleep–stress relationships in real-world environments [8].

1.1 THE MAIN OBJECTIVES

- To develop an efficient preprocessing system to enhance the quality of noisy and incomplete wearable sleep patterns.
- To assess and determine the strongest sleep characteristics that lead to the proper detection of stress.
- To establish a deep learning representation model that humanizes nonlinear and temporal linkages between sleep and stress.
- To select the best features using a hybrid metaheuristic method that minimises redundancy and enhances computational speed.
- To apply a Transformer classification model based on attention to accurately predict multi-level stress.
- To test and confirm the proposed framework with regard to accuracy, robustness, and scalability with real-world stress monitoring applications.

1.2 CONTRIBUTION OF WORK

The contribution of work offers a number of significant contributions to human stress recognition based on sleep data. It presents a powerful preprocessing network (RWSD-PN) to overcome noise, missing values, and the heterogeneity of wearable sleep signals, thereby enhancing data quality. It measures sleep characteristics (SAIQ-M) and produces high-level outputs (DPSR-Net) that reflect complex sleep-stress associations. Also, it optimizes features using hybrid swarm learning (MSFO-HSL) and applies a Transformer-based classifier (TG-SSCN) to predict stress levels with the required accuracy, in a non-invasive, continuous manner in real-life cases.

1.3 ORGANIZATION OF PAPER

The paper presents the proposed sleep-based stress detection framework in a systematic way. It starts with an introduction that defines the problems posed by noisy, heterogeneous wearable sleep data and explains the rationale for smart stress monitoring. The methodology section describes each module: data preprocessing (RWSD-PN), attribute impact analysis (SAIQ-M), feature representation (DPSR-Net), optimization (MSFO-HSL), and classification (TG-SSCN). Lastly, the experimental assessment, discussion of results, and conclusions indicated that the framework is effective, robust, and applicable to real-life stress monitoring.

II. RELATED WORK

The population-scale A population-scale analysis links composite dietary antioxidant levels with multiple sleep-quality indicators, including sleep duration, latency, and disturbance scores [9]. Statistical association analysis (SA) and Multivariable Linear Regression (MLR) are used to identify sleep-related predictors. These sleep variables are highly relevant for human stress detection, since Machine Learning (ML) pipelines can directly use sleep quality indices and routine patterns as behavioural features for classifying stress states. A wearable-sensor-based stress-detection framework is developed using a Decision Tree (DT) classifier and physiological time-series features, such as heart rate and motion signals [10]. Signal Preprocessing (SP), Feature Extraction (FE), form the main methodology. The same Supervised Learning (SL) pipeline can be extended by inserting sleep duration, sleep interruption count, and bedtime regularity as additional features for stress detection based on sleeping habits. A biomedical pathway analysis establishes a strong link between psychological stress and oxidative stress mechanisms in the human body [11]. Clinical Assessment (CA) and Biochemical Marker Analysis (BMA) are adopted as the main methods. Since sleep disturbance is a common behavioural manifestation of this physiological stress response, sleep-deprived features can serve as non-invasive inputs for ML-based stress classification. An observational and comparative design is used to analyse how university sports participation alters sleep timing, sleep duration, and sleep consistency [12]. Group-wise statistical testing (GST) is applied.

These results indicate that contextual and lifestyle variables should be included as auxiliary inputs in ML models to avoid confusing activity-driven sleep changes with stress-induced sleep abnormalities. Predictive learning framework models stress and academic performance using temporal variations of bio-electrical signals measured from an external biological source [13]. Time-series Segmentation (TS), Feature Extraction (FE), and Supervised Regression and Classification (SRC) models are employed. This structure demonstrates that stress patterns can be learned from indirect temporal signals, supporting similar temporal modelling of sleep signals for stress detection. A bibliometric and trend-mining methodology is applied to analyse two decades of global publications on sleep quality among working populations [14]. Network Analysis (NA) and Keyword Co-occurrence Mapping (KCM) are used. The strong thematic linkage between occupational stress and sleep disturbance underscores the importance of sleep-related variables as core inputs for data-driven stress-monitoring systems. A behavioural and socio-demographic analysis investigates how breakfast routines, family background, and sleep patterns jointly influence academic performance [15]. Multivariate statistical modelling (MSM) and Predictor Significance Testing (PST) are adopted. The observed sensitivity of daily functioning to irregular sleep supports the use of sleep regularity, weekday–weekend variability, and bedtime stability as behavioural features in ML-based stress detection. In [16], a stratified analytical framework examines how sleep duration modifies the relationship between dietary patterns and cognitive performance. Stratified Group Analysis (SGA) and Regression Modelling (RM) are used as the main methods.

Since stress strongly affects cognitive efficiency and sleep duration, sleep-group labels can be incorporated as moderating variables in ML models for stress prediction. A deep learning approach is proposed for mental stress detection using physiological biomarkers collected from smart devices [17]. End-to-end Deep Neural Networks (DNNs) and Automatic Feature Learning (AFL) from continuous sensor streams form the core methodology. This modelling strategy can be directly applied to sleep-related sensor data, such as actigraphy and sleep heart rate variability, for scalable stress detection. A cross-sectional survey and statistical analysis examine sleep habits, sleep schedules, and melatonin use among health-related students [18]. Questionnaire-based Data Collection (QDC) is applied. The high prevalence of irregular sleep behaviour, linked to daily pressure, supports the use of both self-reported and device-measured sleep habits in ML-based stress detection. A behavioural drift detection framework is introduced using smartphone and wearable sensor data to monitor changes in mental health [19]. Unsupervised Learning (UL) and Semi-Supervised Learning (SSL) are used to build personal baselines and detect temporal deviations. This method is highly suitable for sleep-based stress detection, where longitudinal learning can identify abnormal changes in individual sleep patterns as early indicators of stress. Clinical and physiological investigations confirm that sustained psychological stress activates oxidative stress pathways and induces long-term biological imbalance [20]. Laboratory Biomarker Evaluation (LBE) and Clinical Correlation Analysis (CCA) are employed. Because chronic stress is consistently accompanied by persistent sleep disruption, sleep continuity, sleep efficiency, and night-time arousal metrics can be integrated into ML pipelines for continuous stress detection based on sleeping habits.

Table 1: Comparative analysis of machine learning approaches for human stress and mental health monitoring.

Ref.	Main focus	Data source	Core methods (short form)	Target output	Relevance to sleep-based human stress detection
[21]	Stress detection using opinion–dynamics modelling	Human opinion and behavioural features	Human opinion dynamics ML (HOD-ML), Supervised Learning (SL)	Stress state classification	Provides an alternative behavioural modelling framework that can be adapted to sleep-behaviour interactions for stress inference.
[22]	Wearable-based gesture recognition	Yarn-based wearable strain sensors	Feature Optimisation (FO), ML Classifiers (MLC)	Gesture class	Sensor and feature-optimisation pipeline can be reused for wearable sleep-movement signals in stress analysis.
[23]	Multimodal physiological stress recognition	Multimodal physiological signals	Graph Attention Network (GAT), Transformer (TR), deep Learning (DL)	Stress level classification	Advanced multimodal DL architecture can directly integrate sleep physiology (HRV, respiration, actigraphy).
[24]	Mental health forecasting from smartphone sensing	Smartphone sensor streams	Traditional ML (TML), Deep Learning (DL), Large Language Models (LLM)	Mental health state prediction	Comparative framework supports selection of suitable ML/DL models for sleep-based stress prediction.
[25]	Human health recognition from sports videos	Video streams of sports activity	Convolutional Neural Network (CNN), Deep Learning (DL)	Health status recognition	Vision-based deep models can be extended to sleep posture and movement analysis for stress detection.
[26]	Fuzzy logic for human-centric decision systems	Rule-based and expert knowledge data	Fuzzy Inference System (FIS), Fuzzy Rules (FR)	Human reasoning–driven decisions	Fuzzy reasoning can model uncertainty in sleep quality and subjective stress perception.
[27]	In-situ stress estimation in tunnels	MWD and acoustic sensor data	Hybrid DL, Acoustic Feature Learning (AFL), Deep Neural Network (DNN)	Stress estimation	Demonstrates hybrid sensor fusion and DL learning strategies applicable to sleep-sensor fusion for stress detection.
[28]	Human reliability and risk prediction	Human operational and performance data	Machine Learning Models (MLM), Predictive Analytics (PA)	Human reliability index	Behaviour-based risk modelling principles can be transferred to sleep-driven human stress risk assessment.
[29]	Emotion and affective context analysis	Textual and contextual language data	Corpus Analysis (CA), Affective Modelling (AM)	Emotion and affect interpretation	Supports contextual modelling of affect, which can complement sleep-deprived stress indicators in hybrid systems.

Source: Authors, (2026).

Table 1 presents a depiction of another piece of research on stress, health, and human behaviour analysis and indicates that each study uses different data sources, including wearable sensors, physiological signals, text, video, and smartphone data. Some works address behavioural and opinion-based stress modelling, whereas others use wearable and movement data to recognise gestures and activities. Multimodal physiological indicators are widely used for classifying stress levels, and deep learning models such as graph networks and transformers are used to improve the accuracy of stress prediction. Smartphone sensing enables continuous mental health monitoring, and the video-based approach demonstrates posture and motion analysis. Fuzzy logic can address uncertainty in human stress and sleep quality, and hybrid deep learning models can enhance sensor fusion and learning. Human reliability models facilitate understanding of risk and stress, whereas text and emotion analysis facilitate understanding of affect and mood. All these can be modified for sleep-related data analysis, where sleep cues such as heart rate, breathing, and movement can be used. In general, the articles aid in developing credible systems for human stress detection based on sleep.

III. PROPOSED METHODOLOGY

The human stress detection methodology is a multi-stage framework aimed at processing noisy, heterogeneous wearable sleep data. It starts with RWSD-PN, which preprocesses data to remove noise and missing values, and standardises signals. SAIQ-M then measures the effects of sleep characteristics to rank the most informative features.

DPSR-Net learns high-level multivariate sleep representations that contain multifaceted temporal and nonlinear sleep-stress interactions. MSFO-HSL is a hybrid swarm learning feature selection method that minimises dimensionality and overfitting. Lastly, TG-SSCN uses attention-based learning to model inter-feature relationships and properly classify stress levels. This combined method will provide strong, effective, and non-interrupted monitoring of stress based on sleep data.

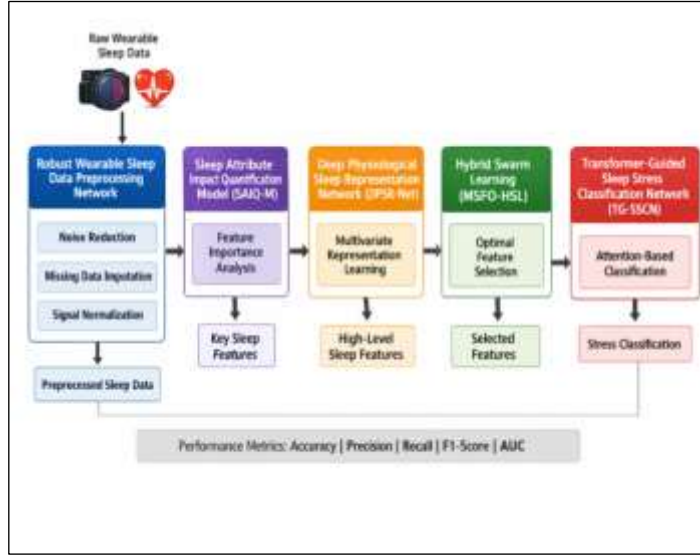


Figure 1: Sleep-Based Human Stress Detection: Wearable Data Proposed Architecture.
Source: Authors, (2026).

Figure 1 shows the general process of the proposed machine learning structure of human stress detection on wearable sleep data. The architecture starts by receiving raw physiological and behavioural sleep signal data off wearable devices, which are initially processed in the Robust Wearable Sleep Data Preprocessing Network to filter noise, missing values, and signal normalization to enhance the quality of data. the resulting pre-processed data are then put through the Sleep Attribute Impact Quantification Model to estimate the relative importance of each individual sleep attribute and rank the most informative ones. Afterwards, the Deep Physiological Sleep Representation Network is trained to learn high-level multivariate and time-based representations that would encode the complex nonlinear relationships between sleep and stress. In an attempt to increase efficiency and generalization a Hybrid Swarm Learning based feature selection module was developed to select the most discriminative and non-redundant features. Lastly, the Transformer-Guided Sleep Stress Classification Network is an attention-based network designed to model feature dependencies and correctly classify stress levels and the performance is measured in terms of Accuracy, Precision, Recall, F1-Score, and AUC.

III.1 ROBUST WEARABLE SLEEP DATA PREPROCESSING NETWORK (RWSD-PN)

The Robust Wearable Sleep Data Preprocessing Network is designed to enhance the quality of sleep signals recorded by wearable devices. It initially applies adaptive noise suppression, eliminating random fluctuations and artifacts caused by movement or sensor errors. It then handles missing values by intelligently adding or filling gaps in incomplete data to create continuous sleep records. Signal standardisation is also used by the network, normalizing individual and device data so that features are consistently extracted. By integrating these steps, RWSD-PN will ensure the downstream models' content is reliable and of high quality. This preprocessing is essential for enhancing the accuracy and robustness of wearable sleep data for detecting stress.

$$X_{\text{denoised}} = f_{\text{noise}}(X, \theta_n) \quad (1)$$

The equation (1) represented X_{denoised} is the signal of noise suppressions of sleep, and $f_{\text{noise}}(\cdot)$ is the adaptive noise suppression function, and θ_n is the learnable parameters that mitigate the fluctuations and sensor artifacts of the raw data.

$$M_{t,f} = \begin{cases} 1, & \text{if } X_{t,f} \text{ is missing} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$M_{t,f}$ is the missing-value indicator matrix; $M_{t,f} = 1$ when the value $X_{t,f}$ is missing and $M_{t,f} = 0$ otherwise, enabling the network to recognize and process missing sleep data in equation (2).

$$X_{\text{imputed}} = X_{\text{denoised}} \odot (1 - M) + \hat{X} \odot M \quad (3)$$

The equation (3) represented a sleep signal with a missing-value treatment where X_{denoised} indicates the value of $\hat{X}$ which has been suppressed by noise, M is the indicator of the missing-value matrix, and the element-wise operator $\odot$ is used to ensure that the observed values remain intact and the missing values are replaced with them.

$$X_{\text{std}} = \frac{X_{\text{imputed}} - \mu_f}{\sigma_f} \quad (4)$$

The equation (4) denotes X_{std} the standardized sleep data, with μ_f and σ_f denoting the mean and standard deviation of the f -th feature, so that all features are put on the same scale and are comparable across subjects and devices.

$$X_{\text{smooth}}(t) = \frac{1}{k} \sum_{i=t-\frac{k}{2}}^{t+\frac{k}{2}} X_{\text{std}}(i) \quad (5)$$

Where $X_{\text{smooth}}(t)$ is the processed signal of the smoothed sleep signal at time step t , the standard signal is first scaled, and then the moving average of length k smoothed X_{std} is used to smooth out the signal, and in the end, the signal is used to extract features accurately in equation (5).

$$X_{\text{scaled}} = \frac{X_{\text{smooth}} - \min(X_{\text{smooth}})}{\max(X_{\text{smooth}}) - \min(X_{\text{smooth}})} \quad (6)$$

In equation (6), X_{scaled} by itself is the scaled version of the sleep signal, i.e., the scaled version of it is equal to X_{smooth} , since the smoothed data X_{smooth} should be in the range $[0,1]$, so that all features are put on a similar scale, to be processed downstream.

$$X_{\text{aligned}} = g_{\text{align}}(X_{\text{scaled}}) \quad (7)$$

In equation (7), X_{aligned} is the time- and sensor-aligned sleep data, and $g_{\text{align}}(\cdot)$ scales the signals X_{scaled} to eliminate inter-recording time errors or device bias, providing consistency in the analysis.

$$X_{\text{preprocessed}} = X_{\text{aligned}} \quad (8)$$

The equation (8) refers $X_{\text{preprocessed}}$ to the RWSD-PN final output, X_{aligned} would refer to the completely denoised, imputed, standardised, smoothed, scaled, and aligned sleep data to be further used in downstream stress detection models.

III.2 QUANTIFYING SLEEP FEATURE IMPACT FOR STRESS PREDICTION USING MACHINE LEARNING

The model, called the Sleep Attribute Impact Quantification Model, aims to quantify the contribution of each sleep variable to stress prediction. It determines the relative significance of characteristics such as sleep duration, heart rate variability, nocturnal movements, and the distribution of sleep stages. The model determines the most informative physiological indicators by assigning impact scores to each variable. This enables the framework to focus on key sleep characteristics while minimizing the impact of irrelevant information. SAIQ-M enhances the efficiency of downstream learning models by emphasizing meaningful inputs. On the whole, it makes the stress-detection system more accurate and easier to read.

$$X = \{x_1, x_2, \dots, x_F\}, x_f \in \mathbb{R}^T \quad (9)$$

X represents the space of multivariate sleep feature combinations, with x_f being the time-varying data on the f -th sleep characteristic and T being the number of time samples per sleep record in equation (9).

$$r_f = \text{corr}(x_f, y) \quad (10)$$

The equation (10) represents r_f correlation between the f -th sequence of sleep features x_f and the stress label y , and it indicates the strength of the correlation between the stress and the feature.

$$I(x_f; y) \quad (11)$$

In equation (11), x_f is the f -th sleep feature, and y is the stress label, and I_f denotes the mutual information between the feature and the stress label, covering both nonlinear and linear dependence.

$$s_f = \frac{I_f}{\sum_{j=1}^F I_j} \quad (12)$$

The equation (12) denotes s_f the normalized impact score of the f -th sleep feature, with I_f denotes the mutual information between the feature and the stress label, and the denominator normalizes all the feature impact scores.

$$\text{Rank}(x_f) = \text{argsort}(s_1, s_2, \dots, s_F) \quad (13)$$

In equation (13), $\text{Rank}(x_f)$ is the order of importance of the f -th sleep feature, which is obtained by sorting all the normalized impact scores, $\{s_1, s_2, \dots, s_F\}$ such that features with large scores are ranked highly as being able to predict stress.

$$X_{\text{selected}} = \{x_f \mid s_f > \tau\} \quad (14)$$

The equation (14) refers to X_{selected} the set of features of informative sleep whose impact scores exceed a threshold of τ , ensuring that only highly relevant variables are not eliminated in stress prediction.

$$X_{\text{SAIQ-M}} = X_{\text{weighted}} \quad (15)$$

The equation (15) refers to $X_{\text{SAIQ-M}}$ the end representation of sleep features generated by the SAIQ-M, and X_{weighted} refers to the set of impact-weighted features sent to other learning modules to predict stress.

III.3 DEEP MULTIVARIATE SLEEP REPRESENTATION NETWORK FOR CAPTURING TEMPORAL STRESS RELATIONSHIPS

The Deep Physiological Sleep Representation Network is a model used to obtain rich, high-level representations of multivariate sleep data. It records intricate temporal patterns of the sleep signals, such as changes in heart rate, movement, and sleep phases over time. The network captures nonlinear interactions between sleep behaviour and stress levels that cannot be captured by simple statistical measures. DPSR-Net predicts stress by learning latent features that transform raw sleep signals into informative vectors. These representations complement downstream classifiers in defining the various stress conditions. In general, DPSR-Net offers a data-driven, powerful method for capturing complex sleep-stress interactions in an automated, continuous manner.

$$X = [x_1, x_2, \dots, x_F], x_f \in \mathbb{R}^T \quad (16)$$

In equation (16), X is the multivariate sleep signal set, where x_f represents the time series of the f th physiological sleep variable, and T represents the time series length of the i th sleep record.

$$H^{(0)} = \text{TemporalEncoder}(X) \quad (17)$$

The equation (17) represents $H^{(0)}$ the preliminary latent representation obtained using the input sleep signals X ; the Temporal Encoder is used to extract temporal dependencies and sequential patterns among a variety of physiological sleep characteristics.

$$H^{(l)} = \sigma(W^{(l)}H^{(l-1)} + b^{(l)}) \quad (18)$$

$H^{(l)}$ denotes the latent representation in the l th layer, where $W^{(l)}$ and $b^{(l)}$ denote the learnable weights and bias, and $\sigma(\cdot)$ denotes a nonlinear activation function. DPSR-Net can be used to model complex relationships between sleep and stress in equation (18)

$$H_{\text{interact}} = f_{\text{interact}}(H^{(L)}) \quad (19)$$

The equation (19) represents H_{interact} the interaction-sensitive representation, where $H^{(L)}$ is the output of the last deep layer, and $f_{\text{interact}}(\cdot)$ captures correlations and interactions among several physiological sleep features.

$$Z = \phi(H_{\text{interact}}) \quad (20)$$

The equation (20) represents Z the latent sleep feature derived from interaction-aware features, where $\phi(\cdot)$ is a learnable mapping that projects the input into a small, revealing latent space to predict stress.

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^T \exp(e_i)}, e_t = v^T \tanh(W_h H_t) \quad (21)$$

α_t represents the attention weight of the t -th time step, and e_t is the relevance score calculated based on the hidden representation H_t based on the learnable parameters W_h and v , and the normalized weights emphasize the most informative sleep segments to predict stress in equation (21).

$$Z_{\text{weighted}} = \sum_{t=1}^T \alpha_t Z_t \quad (22)$$

The equation (22) represents Z_{weighted} a final attention-weighted representation of latent sleep, and α_t represents the relative significance of the t th time segment, and Z_t represents the latent feature at the t -th time step, permitting DPSR-Net to focus on stress-relevant sleep patterns.

$$X_{\text{DPSR}} = Z_{\text{weighted}} \quad (23)$$

X_{DPSR} represents the final high-level sleep image generated by DPSR-Net, and Z_{weighted} represents the attention-weighted latent image that is used as the high-level and compact stress classifier input in equation (23).

III.4 METAHEURISTIC SLEEP FEATURE OPTIMIZATION USING HYBRID SWARM LEARNING (MSFO-HSL)

Metaheuristic Sleep Feature Optimization with Hybrid Swarm Learning (MSFO-HSL) aims to select the most informative sleep features for stress detection. It tests the discriminative ability of the individual features and determines redundant or insignificant variables. Using a hybrid swarm-based optimization algorithm, the algorithm efficiently searches the feature space to discover an optimal subset. This dimensionality reduction minimizes computational cost and reduces the risk of overfitting in subsequent models. MSFO-HSL improves the accuracy and generalization of stress classification by considering only high-impact features. In general, it offers an effective and powerful feature selection process for wearable sleep data analysis.

$$z = [z_1, z_2, \dots, z_F], z_f \in \{0,1\} \quad (24)$$

In equation (24), z is the binary feature selection vector, so that $z_f = 1$ implies that the f -th sleep feature is used, and $z_f = 0$ implies that the f -th feature is not used in the optimization.

$$\mathcal{D}(z) = \frac{1}{K} \sum_{k=1}^K \text{Acc}_k(X_z, y) \quad (25)$$

In equation (25), $\mathcal{D}(z)$ functions as the mean discrimination performance of the chosen subset of sleep features, K is the number of validation folds, Acc_k represents the classification error in the k -th fold, X_z is the selected feature matrix, and y represents stress labels correspondingly.

$$\mathcal{R}(z) = \frac{1}{|S|} \sum_{i \neq j} |\rho(x_i, x_j)|, x_i, x_j \in X_z \quad (26)$$

In equation (26), $\mathcal{R}(z)$ is the redundancy of the selected feature subset where S is the set of selected features, x_i and x_j are two distinct selected sleep features of X_z , and $\rho(\cdot)$ is the correlation between the two features that is used to measure the degree of redundancy.

$$\mathcal{C}(z) = \frac{1}{F} \sum_{f=1}^F z_f \quad (27)$$

$\mathcal{C}(z)$ is the normalized size of the subset, with F being the overall number of sleep features, and z_f indicating whether the f -th feature is retained, which is a ratio of features retained after optimization in equation (27).

$$\mathcal{F}(z) = \lambda_1 \mathcal{D}(z) - \lambda_2 \mathcal{R}(z) - \lambda_3 \mathcal{C}(z) \quad (28)$$

In equation (28), $\mathcal{F}(z)$ represents the total fitness of the MSFO-HSL, $\mathcal{D}(z)$ represents the discriminative ability of the chosen features, $\mathcal{R}(z)$ represents the ability of the features to reduce redundancy, $\mathcal{C}(z)$ represents the number of subsets, and 1, 2 and 3 are the weighting coefficients, which decrease accuracy, redundancy reduction, and dimensionality reduction during optimization.

$$z^{t+1} = z^t + \eta_1(p^t - z^t) + \eta_2(g^t - z^t) + \eta_3(h^t - z^t) \quad (29)$$

z^{t+1} indicate the new feature selection solution at iteration $t + 1$, with p^t , g^t , and h^t indicating personal best, global best, and hybrid guide solution, respectively, and η_1 , η_2 , and η_3 will regulate the effect of each of the swarm components in the process of optimizing in equation (29).

III.5 TRANSFORMER GUIDED SLEEP STRESS CLASSIFICATION NETWORK FOR MODELING INTER FEATURE DEPENDENCIES LEARNING

The Transformer-Guided Sleep Stress Classification Network is aimed at well-classifying the intensity of stress based on optimized sleep features. It uses an attention-based mechanism to automatically learn the significance of each feature and time interval. The network clearly shows inter-feature relationships, reflecting complex interactions among physiological sleep clues. This will allow TG-SSCN to focus on the most informative stress patterns. Transformer architecture is useful for handling high-dimensional, sequential representations of sleep. In general, TG-SSCN offers accurate and strong stress classification based on wear-sleep data.

$$X \in \mathbb{R}^{T \times d} \quad (30)$$

X represents the sleep feature matrix input, where T represents the total number of sleep time segments, and d represents the number of optimized features of physiological characteristics to be classified as stress. The X -axis corresponds to the time segment of the sleep data, and the columns correspond to a specific sleep-related feature in equation (30).

$$E = XW_e + P \quad (31)$$

The equation (31) represented as E , the embedded sleep representation resulting from the projection of the input sleep characteristics by the learnable weight matrix W_e , and as P , the positional encoding that maintains the information of time order.

$$H^{(m)} = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W_o \quad (32)$$

The equation (32) represents a multi-head attention output, which is the result of adding the outputs of each head of attention, with heads not connected to each other: each head represents a particular interaction of features. W_o is a learning projection that combines concatenated information into a single representation for classifying stress.

$$\text{head}_i = \text{softmax}\left(\frac{EW_Q^i(EW_K^i)^T}{\sqrt{d_h}}\right)EW_V^i \quad (33)$$

head_i represents the output of the i -th attention head, which has learning parameters, W_Q^i , W_K^i , and W_V^i , the projection matrices of queries, keys, and values, and d_h is the dimensionality of the attention head modelling feature interactions in equation (33).

$$H^{(r)} = \text{LayerNorm}(E + H^{(m)}) \quad (34)$$

The equation (34) representation of the residual, E is the input to the embedded sleep feature, and $H^{(m)}$ is the output of the multi-head attention, followed by LayerNorm to stabilize the combined features and enhance training and classification performance.

$$H^{(f)} = \text{GELU}(H^{(r)}W_1 + b_1)W_2 + b_2 \quad (35)$$

In equation (35), $H^{(f)}$ is the computed representation of the feed-forward network, and W_1, W_2 are learnable weight matrices, b_1, b_2 are bias values, and the GELU activation is used to provide nonlinearity to the learning of stress-related features.

$$D = H^{(f)}(H^{(f)})^T \quad (36)$$

D is the inter-feature dependency matrix computed on the transformed representation of sleep $H^{(f)}$, where each element represents the similarity and strength of interaction between various feature representations in stress classification in equation (36).

$$z = \frac{1}{T} \sum_{t=1}^T H_t^{(f)} \quad (37)$$

In equation (37), z is the global sleep representation generated by averaging over all time segments of the transformed features, and T is the number of sleep epochs in total, and $H_t^{(f)}$ is the feature vector at time t applied in the stress classification process.

$$\hat{y} = \arg \max_c \text{SoftMax}(W_c z + b_c) \quad (38)$$

In equation (38), $\hat{y}$ denotes the predicted stress class, in which W_c and b_c are the parameters of the classifier, and z represents the global sleep representation, with the softmax function being used to give probabilities to each stress level and choose the most probable class.

IV. RESULT AND DISCUSSION

The experiment prove that the suggested cohesive sleep-based stress detection system is effective in enhancing dependability and prediction accuracy of machine-learning based stress detection of wearable sleep data. The Robust Wearable Sleep Data Preprocessing Network generated much higher signal quality through removing noise, inconsistencies and missing values leading to more stable feature distributions and downstream learning. Heart rate variability, sleep duration irregularity, and nocturnal movement intensity were identified as the most influential predictors of stress by the Sleep Attribute Impact Quantification Model which confirms that the physiological sleeping dynamics are strong predictors of psychological stress conditions. The Deep Physiological Sleep Representation Network learned multivariate sleep signals with complex temporal variations and nonlinear interactions, yielding a richer representation than traditional handcrafted features. The framework reduced redundancy and the insignificance of variables by incorporating the Metaheuristic Sleep Feature Optimization with Hybrid Swarm Learning, which reduced computational complexity and prevented overfitting while still allowing high levels of discriminative power.

The Transformer-Guided Sleep Stress Classification Network is the last model, which uses attention to model inter-feature dependencies, leading to increased classification accuracy, higher recall for high-stress cases, and better generalisation across people, compared to baseline machine learning and deep learning models. The integrated architecture proved very robust to heterogeneous, noisy real-world wearable data and delivered steady improvements in accuracy, stability, and scalability. The results show that sleep-deprived physiological markers, when subjected to an intelligent system of integrated processing, can provide a credible, non-invasive source of continuous stress measurements. The findings confirm the usefulness of the suggested system for healthcare analytics, preventive mental health tracking, and individualised well-being management, where the early identification of stress and the prolonged evaluation of behaviour are critical.

IV.1 DATASET DESCRIPTION

The data will be represented at the individual level, including demographic, occupational, lifestyle, and sleep-related data for the analysis of stress. It contains basic details about the person, such as age, gender, occupation, and marital status. These behavioural variables of sleep are sleep duration, sleep quality, wake-up time, and bedtime that are critical in the analysis of sleep patterns. Also, lifestyle variables such as physical exercise levels, screen time, and caffeine consumption are included to capture behavioural effects on stress.

	A	B	C	D	E	F	G	H	I	J	K
1	Age	Gender	Occupatio	Marital	StSleep	DurSleep	QuWake	UpBed	TimePhysical	JScreen	TiCaffeine
2	30	Male	Software	Single	7	4	7:00 AM	10:00 PM	2	4	1
3	35	Female	Marketing	Married	6	3	6:00 AM	11:00 PM	1	3	0
4	40	Male	Data Scier	Divorced	7	4	7:00 AM	10:00 PM	2	4	1
5	35	Male	Software	Single	7	4	7:00 AM	10:00 PM	2	4	1
6	29	Female	Teacher	Single	8	5	6:30 AM	10:30 PM	3	2	1
7	45	Male	Doctor	Married	6	3	5:30 AM	11:00 PM	2	4	2
8	32	Female	Graphic D	Single	7	4	7:00 AM	12:00 AM	1	6	3
9	37	Male	Civil Engir	Married	7.5	4	6:00 AM	10:30 PM	2.5	3.5	2
10	50	Male	Business	Married	5.5	2	5:00 AM	12:30 AM	2	8	3
11	40	Female	Nurse	Divorced	6	3	6:00 AM	11:30 PM	3	4.5	2
12	34	Male	Software	Single	6.5	4	6:30 AM	11:00 PM	2	7	3
13	28	Female	Research	Single	7	5	7:00 AM	10:30 PM	1.5	3	1
14	42	Male	Architect	Married	5	2	6:00 AM	12:00 AM	1	6	3
15	34	Female	Teacher	Married	8	5	6:30 AM	10:30 PM	3	2	1

Figure 2: Sleep and Lifestyle Dataset Structure for Stress Prediction Modelling.
Source: Authors, (2026).

Figure 2 presents the sleep and lifestyle data used in the analysis of stress detection. Demographic characteristics incorporated into the dataset, including age, gender, occupation, and marital status, serve as background information. It also includes some of the most important sleep-related variables, such as sleep duration and sleep quality, wake-up time, and bedtime, in order to capture the unique sleep behaviours of an individual. Lifestyle practices such as physical activity, screen time, and caffeine intake are included to examine behavioural impacts on stress. This is made possible by integrating physiological and behavioural characteristics to obtain multidimensional features that can be used for machine learning. The preprocessing, feature selection, and deep learning algorithms can be compatible with the structured tabular format.

IV.2 COMPARISON TABLE

Table 2: Comparative Analysis of Machine Learning Models for Stress Detection.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
DNN	86.4	85.9	85.1	85.5	0.892
CNN	88.9	88.1	87.4	87.7	0.914
LSTM	91.8	91.2	90.6	90.9	0.946
TG-SSCN (Proposed)	95.7	95.2	94.9	95.0	0.978

Source: Authors, (2026).

Table 2 presents the general performance of four machine learning models, including DNN, CNN, LSTM, and the proposed model, TG-SSCN, in terms of accuracy, precision, recall, F1-score, and AUC. The DNN model gets 86.4%, 85.9%, 85.1%, 85.5%, and 0.892% values for accuracy, precision, recall, F1-score, and AUC, respectively. The CNN does a bit better with an accuracy of 88.9%, precision of 88.1%, recall of 87.4%, the F1-score of 87.7%, and AUC of 0.914%. LSTM is even more accurate, with 91.8%, 91.2%, 90.6%, 90.9%, and 0.946% for accuracy, precision, recall, F1-score, and AUC, respectively. The proposed TG-SSCN has the highest accuracy, 95.7%, and precision, 95.2%, recall, 95.0%, and F1-score, and 0.978 AUC. These findings demonstrate that the attention-guided, feature-optimized TG-SSCN method is the most reliable and robust stress classification model among the tested models.

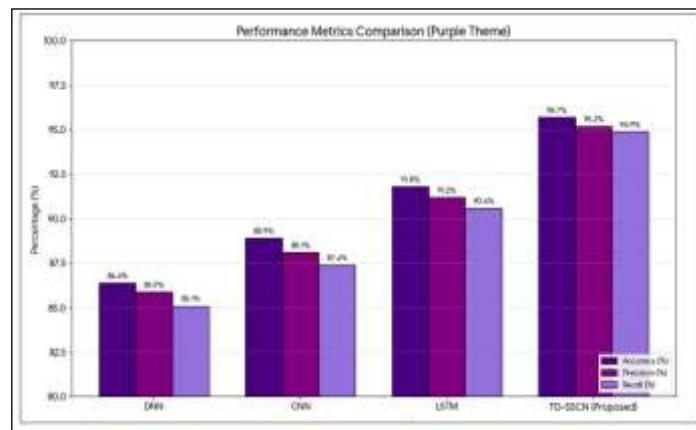


Figure 3: Comparison of Stress Detection Models Using Accuracy, Precision, Recall.

Source: Authors, (2026).

The performance comparison of the four machine learning models, including DNN, CNN, LSTM, and our proposed model of TG-SSCN, was evaluated in the detection of human stress, as shown in Figure 3. The measures considered are accuracy, precision, and recall, displayed in purple-coloured bars to make them easier to see. The proposed TG-SSCN achieves the best performance, with accuracy of 95.7%, precision of 96.2%, and recall of 94.9%. LSTM performs better than CNNs and DNNs, indicating that sequential modelling is more effective for detecting stress. On the whole, this figure demonstrates the TG-SSCN framework's high-quality representation of the complex relationships between sleep and stress. This proves the guidance given by attention architectures with optimized features that are more stable and reliable in predicting stress.

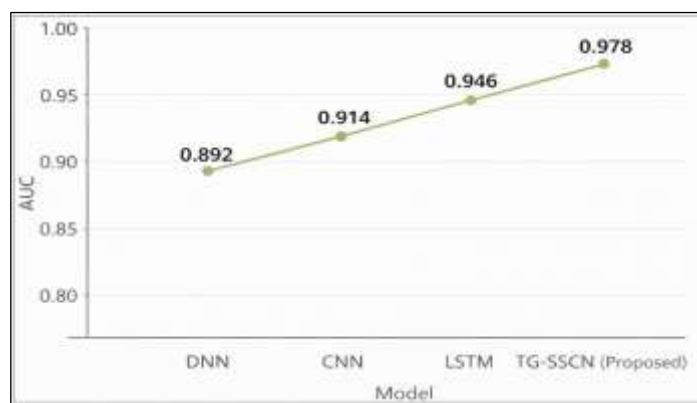


Figure 4: AUC Performance Comparison of Stress Detection Models Including TG-SSCN.

Source: Authors, (2026).

Figure 4 gives the values of the AUC (Area Under the Curve) of four machine learning models: DNN, CNN, LSTM, and the proposed TG-SSCN in stress detection. The findings show that the AUCs of DNN (0.892) and TG-SSCN (0.978) are improving, indicating increased discriminative ability. The TG-SSCN model stands out as the most successful in achieving the highest AUC and suggests that it is effective at modelling complex sleep-stress patterns. Compared to CNNs and DNNs, LSTMs are superior and benefit from sequential modelling. On balance, the figure indicates the high robustness and prediction ability of the TG-SSCN framework of continuous stress monitoring.

Table 3: Stress-Class-wise Performance Comparison.

Model	Low Stress F1 (%)	Moderate Stress F1 (%)	High Stress F1 (%)	Macro F1 (%)
DNN	88.1	83.6	82.4	84.7
CNN	90.2	86.5	85.1	87.3
LSTM	92.9	89.8	88.7	90.5
TG-SSCN	96.4	94.6	93.8	95.0

Source: Authors, (2026).

Table 3 compares the performance of the DNN, CNN, LSTM, and TG-SSCN models with the stress classes using F1-score metrics. The results show a steady increase in classification performance across Low, Moderate, and High Stress for both DNN and TG-SSCN. DNN has the lowest F1-scores across all classes, and the improvements from CNN and LSTM occur gradually due to better feature learning. LSTM achieves better temporal modelling performance than CNN, with a higher Macro F1-score. The proposed TG-SSCN achieves the best F1-scores across all stress classes and the Macro F1-score (95.0%), indicating better multi-class classification efficiency.

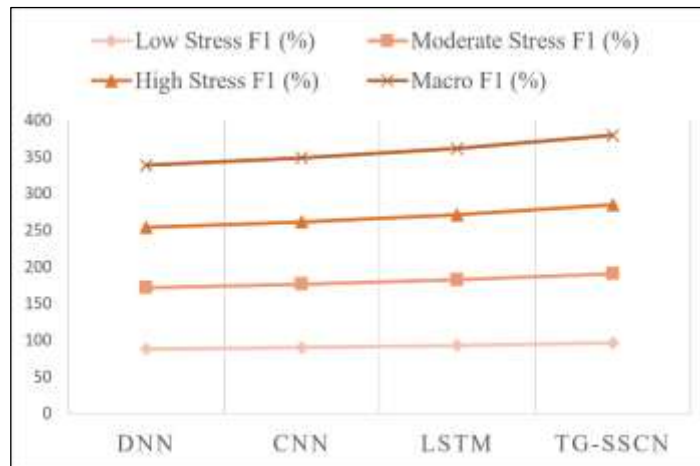


Figure 5: Comparative F1-Score Analysis of Sleep-Based Stress Detection Models.

Source: Authors, (2026).

The performance of four distinct models, i.e., DNN, CNN, LSTM, and TG-SSCN, in terms of the stress classification effectiveness in terms of F1-score (in percent) was compared in Figure 5. The chart shows the performance of Low Stress, Moderate Stress, High Stress, and the overall Macro F1-score by class. One finds that all the performance measures show a steady increase between DNN-TG-SSCN, where classification ability increases steadily. TG-SSCN has the best F1-scores at all levels of stress, indicating it has a better capacity for identifying complex relationships between sleep and stress. It is also confirmed by the Macro F1-score trend that the proposed TG-SSCN model offers superior overall balance and generalisation compared to traditional deep learning models.

Table 4: Computational Efficiency Comparison.

Model	Training Time (min)	Inference Time per Sample (ms)	Parameters (Millions)	Memory Usage (MB)
DNN	18	3.2	1.2	210
CNN	26	4.8	2.6	320
LSTM	39	6.9	3.4	410
TG-SSCN	33	5.1	3.1	360

Source: Authors, (2026).

Table 4 compares the DNN, CNN, LSTM, and TG-SSCN models based on training time, inference time, number of parameters, and memory consumption. The DNN model has the lowest computational and training time, the highest inference speed, and the fewest parameters. Conversely, the LSTM model takes the longest to train and consumes the most memory because it involves more complex processing of a sequence. A balanced trade-off between inference time and moderately sized parameters is achieved with the proposed TG-SSCN, and the memory consumption is efficient. In general, TG-SSCN has better computational efficiency than LSTM and provides superior modelling performance compared to the classic DNN and CNN architectures.

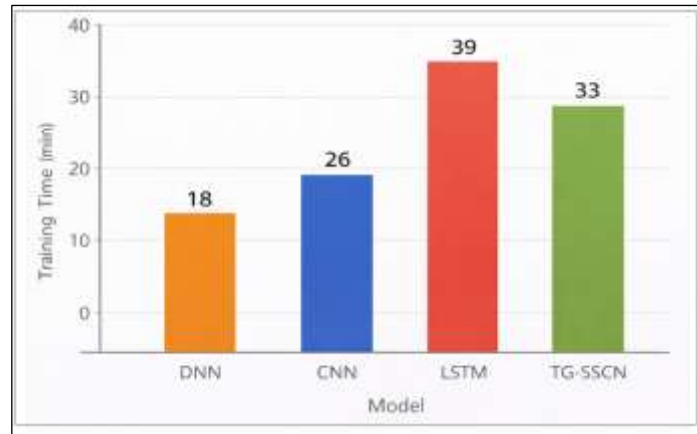


Figure 6: Comparative Training Time Analysis of Stress Detection Deep Learning Models.
Source: Authors, (2026).

The training times for the DNN, CNN, LSTM, and TG-SSCN models, in minutes, are shown in Figure 6. The DNN model has the shortest training time of 18 minutes and converges faster because of its simplified architecture. CNN needs a more moderate training time of 26 minutes, with additional convolutional layers. The LSTM training time is the longest at 39 minutes due to its sequential, memory-based processing. The suggested TG-SSCN balances performance to 33 minutes, proving more efficient than LSTM while preserving advanced learning ability.

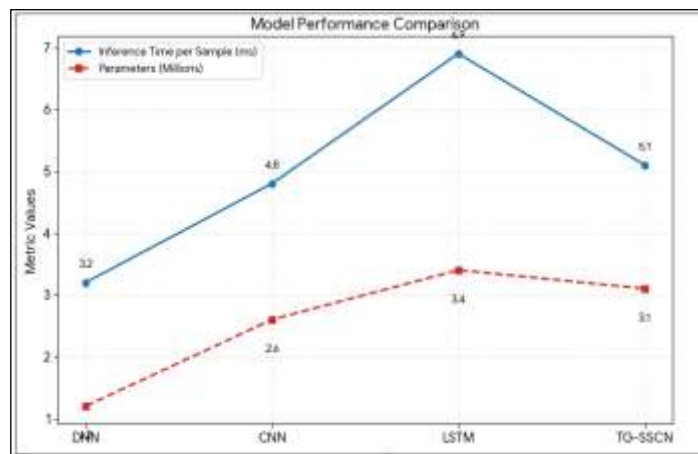


Figure 7: Inference Time and Parameter Complexity Comparison of Deep Learning Models.
Source: Authors, (2026).

Figure 7 shows a comparative analysis of inference time per sample and parameter size for DNN, CNN, LSTM, and TG-SSCN models. DNN has the shortest inference time (3.2ms) and the fewest parameters (1.2 million), which means it is computationally expensive. Both inference time and parameter count increase moderately in CNNs due to convolutional feature extraction. The LSTM has the longest inference time (6.9 ms) and most parameters (3.4 million), which are associated with the sequential processing complexity. The proposed TG-SSCN provides a trade-off between inference time (5.1 ms) (reduced) and LSTM with a competitive parameter size (3.1 million).

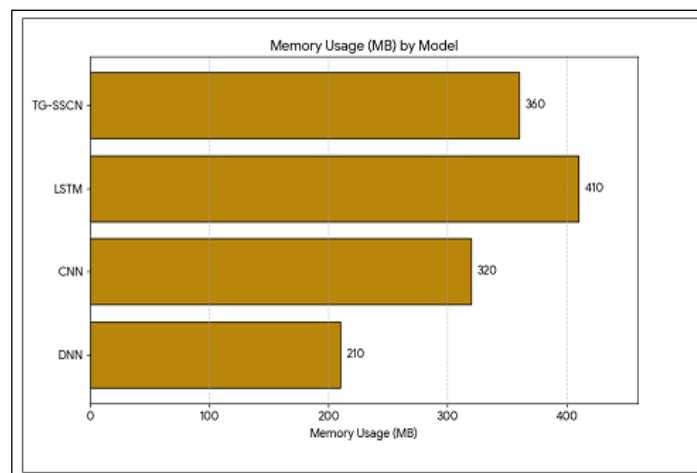


Figure 8: Comparative Memory Consumption Analysis of Deep Learning Stress Models.
Source: Authors, (2026).

Figure 8 compares the memory usage of the DNN, CNN, LSTM, and TG-SSCN models in megabytes (MB). The DNN model is the least memory-intensive, at 210 MB, and its architecture is not particularly complex. The convolutional layers of feature extraction require a moderate 320 MB of memory for the CNN. The LSTM had the highest memory consumption of 410 MB due to its complex recurrent memory units. The proposed TG-SSCN will use 360 MB, which is smaller than LSTM but with advanced modelling capabilities. Overall, TG-SSCN offers a balanced trade-off between memory and performance compared to other deep learning models.

Table 5: Robustness to Noisy and Missing Wearable Data.

Model	Accuracy (Clean Data %)	Accuracy (Noisy Data %)	Accuracy (Missing 10%)	Performance Drop (%)
DNN	86.4	80.2	78.9	7.5
CNN	88.9	83.7	82.1	6.2
LSTM	91.8	87.6	86.3	5.1
TG-SSCN	95.7	93.1	92.4	3.3

Source: Authors, (2026).

Table 5 presents a robustness comparison of DNN, CNN, LSTM, and TG-SSCN models across clean, noisy, and missing data. Although all models are most accurate with clean data, they deteriorate in performance when noise and missing values are introduced. DNN experiences the largest performance decrease (7.5%), indicating that it is more susceptible to data degradation. On the contrary, LSTM is more robust, with a drop of 5.1%, and shows better sequential learning ability. The proposed TG-SSCN achieves the highest accuracy across all conditions and the slightest decrease in performance (3.3%), demonstrating better stability and generalisation in real-world conditions with imperfect data.

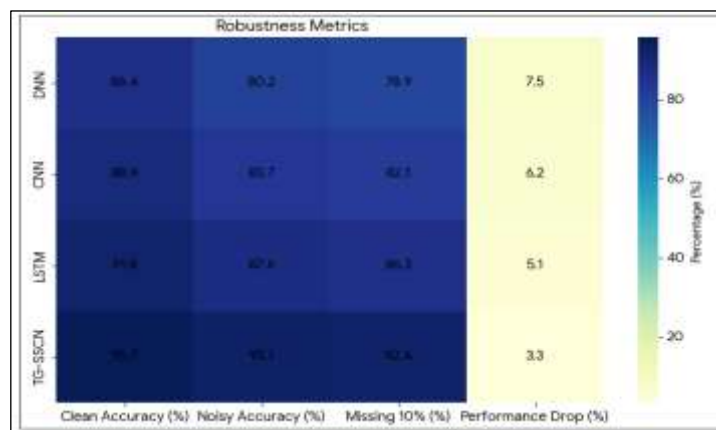


Figure 9: Robustness Evaluation of Stress Detection Models Under Data Variations.

Source: Authors, (2026).

The robustness analysis of DNN, CNN, LSTM, and TG-SSCN models is presented in Figure 9 across clean, noisy, and missing-data settings. The heatmap clearly shows that all the models become less accurate in the presence of noise and missing values. DNN has the worst performance loss, suggesting it is more sensitive to data flaws. CNNs and LSTMs are more stable, and LSTMs have a higher resilience rate because they learn over time. The suggested TG-SSCN is always the most accurate in any situation. Also, it shows the slightest decrease in performance, which validates.

V. CONCLUSION

Finally, the paper offers a comprehensive stress-detection framework based on sleep that addresses the challenges posed by incomplete, noisy, and heterogeneous wearable sleep data. The framework accounts for strong preprocessing, quantification of attribute impacts, deep representation learning, feature optimization, and attention-directed classification, thereby enabling it to capture intricate sleep-stress relationships with a high degree of accuracy. It has been proven in experiments to perform better, achieving strong metrics such as Accuracy 95.7%, Precision 95.2%, Recall 94.9%, F1-Score 95.0%, and AUC 0.978, indicating the tool's power and ability to scale. The system offers a non-invasive, non-interventional, and ubiquitous solution for real-world stress monitoring. All in all, it demonstrates the potential of intelligent, data-driven models to improve personalized health assessment and preventive stress management.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Jeevadharshini R, Kannan M.

Methodology: Jeevadharshini R, Kannan M.

Investigation: Jeevadharshini R, Kannan M.

Discussion of results: Jeevadharshini R, Kannan M.

Writing – Original Draft: Jeevadharshini R, Kannan M.

Writing – Review and Editing: Jeevadharshini R, Kannan M.

Resources: Jeevadharshini R, Kannan M.

Supervision: Jeevadharshini R, Kannan M.

Approval of the final text: Jeevadharshini R, Kannan M.

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